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Estimation of Remaining Useful Life of Bearings based on Support Vector Regression

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Abstract

The overall performance metric of rotating machineries are governed by the reliability of bearings. Bearings are vital components for all moving parts. It has its presence in most of the equipments and machineries. Also, these bearings contribute to most of the failures or breakdowns in an industry. Failures can be reduced to a greater extent by selecting appropriate bearings that suit to the application. Nevertheless, after selection of right bearings, the failure in the bearings tops the list. It becomes complicated when we want to trace out the reasons for failures. Condition monitoring techniques are being deployed in order to increase the uptime of the machineries. **Objectives**: Strengthening the predictive maintenance by estimating the remaing useful life of bearings. **Method**: This paper proposes a predictive model to address the remaining life of the bearing that suits to a real time application. This method is validated on a laboratory experiment wherein the bearing is tested till it fails naturally at stated conditions. **Findings:** Thus obtained results show the model built using Support Vector Regression method proves to be effective in predicting the remaining life of the bearings. **Applications/Improvements**: The proposed predictive model is validated with the new set of data taken from experiments. This model can be deployed in critical real time applications where the bearing failure affects the performance of the machine. Addittionaly this model can be horizontally deployed for other critical components where continuous monitoring is essential.

Keywords : Remaining Useful Life (RUL), Statistical Methods, Support Vector Regression (SVR)

1. Introduction

Rotating equipment's are most widely used in the manufacturing industries and very high percentages of maintenance capital expenses are incurred on the bearings. Bearings are often held responsible for the machine failures. However, there are a number of different problems due to which the bearings have failed like bearing not fitted properly, meaning misalignment, shaft running unbalanced, temperature, excess vibration in the shaft, improper lubricants, selection of right bearing for the application suitable for the load and speed requirements, etc. In a real time environment when we encounter a problem we tend to replace the bearing before fixing the root cause of its failure. Bearing life prediction plays a vital role in improving the plant unscheduled downtime. The objective of deploying a condition based maintenance is to precisely estimate the operating conditions of the machine or the remaining useful life so that the uptime of the machines is improved.

A. Palmgren and G. Lundberg[1-3] have laid foundation in estimating the lifetime of the bearing. This has given way to establish the standard for predicting the lifetime of the bearings with respect to the loads and speed of the application[4-6]. A bearing is said to be damaged when it generates increased noise and vibration and also the temperature of the lubricant increases drastically. Apart from this the bearing damages will be reflected when we monitor the bearings using the vibration signals. The spikes and the amplitude of the signals reveal the damages on the bearing. There are a number of methods/techniques deployed in diagnosing the bearing faults. Further to this, there are more researches done on predicting the life time and the health of the bearing using the defect

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diagnosis methods. Kim, Andy, Mathew, Eric and Choi[7] proposed a prognostic model for precisely assessing the remaining life of bearings based on the health condition monitoring data. This experiment was done using Support Vector Machines (SVM). Case studies from high pressure Liquefied Natural Gas (LNG) pumps were used for diagnosis to validate the defined model. Kankar, Satish Sharma and Harsha[8] also detailed in their papers on the effectiveness of support vector machines on bearing prognosis. The major limitation of this method is that feature extraction and fault classification cannot be modeled to match the real time environment.

Pan, Chen and Dong[9], proposes a hybrid model to estimate the bearing degradation process by integrating the Support Vector Data Description (SVDD) and Fuzzy C-Means (FCM). This model was validated for the feasibility and for the accuracy of the prediction results with the data from the accelerated bearing life test. Zhinong Li, Yongyong He, Fulei Chu, Jie Han[10], proposes the use of Mixtures of Gaussians Hidden Markov Model (MoGHMM) for bearing prognosis. This model is developed with extracted features to determine the health condition of the bearing in off-line. Meanwhile the fault diagnosis and prognosis are manipulated online by estimating the asset's current health condition and determining the remaining useful life of bearings from the developed models. However the model needs to be evaluated to match to the real time environment. The method proposed by Francesco Di Maio, Kwok Leung Tsui, and Enrico Zio[11] is used to estimate the remaining useful life of the bearing by integrating the data-driven approach and model-based techniques respectively. The two techniques that are selected are (i) Relevance Vector Machines for choosing a low number of noteworthy basis functions, called Relevant Vectors and (ii) exponential regression to calculate and constantly revise the remaining life estimations. The grouping of these techniques is validated and established with reference to partially degraded bearings which are tested under accelerated conditions. The proposed case study out performs other model based methods in the life predictions. The proposed model is based on the analyzed data for bad/good conditions in two dimensional space, feature -load/rotation speed. This been proven experimentally for the first time that there are two types of susceptibility characteristics related to the type of a fault. Machine learning techniques were deployed for fault diagnosis. Muralitharan and Sugumaran[12-14] has detailed the feature extraction process from the vibration signals and Srimani and Shanmuga priya[15,16] detailed the application of health monitoring of bearings.

2. Methodology

This paper proposes the below laid step by step process to estimate the Remaining useful Life of the bearings as shown in Figure 1. The Experiments were conducted on dedicated test rigs with real time conditions. The selected bearings were tested on these experimental setups and the vibration signals are acquired at defined intervals. The signals are later converted to data for further analysis.

Statistical features were deployed for feature extraction. These features are dealt in detail in the next sections in this paper. From the listed features the best performing and contributing features are selected. This selection is done using decision tree algorithms. The selected features are further used for constructing a model which will be used for assessing the current state of the bearings and thus estimating the remaining useful life of the bearings in the test.

3. Experimental Procedure

The experiments were conducted with the selected bearings in a controlled environment and run-to-failure test data is aquired to validate the effectiveness of the proposed model for predicting the remaining life of the bearing. In general, most of the bearing tests will be done in an accelerated conditions to the shorten the test time. This paper is built around to overcome the limitations set in the previous researches. The experiments on these bearings are continued at real time environments till the bearing fails naturally. The complete experimental setup used for data acquisition is shown in Figure 2. This setup consists of a bearing, accelerometer, motor, DAQ card and lab VIEW software loaded into a computer to acquire the vibration signals.

The bearings are mounted on a shaft with housing and in-turn connected to a variable speed motor. Few major parameters like speed, load, temperature, lubrication, *etc.,* are simulated at real time conditions. The brand new bearing (ball bearing 6205) are made to run

Figure 1. Methodology of RUL estimation.

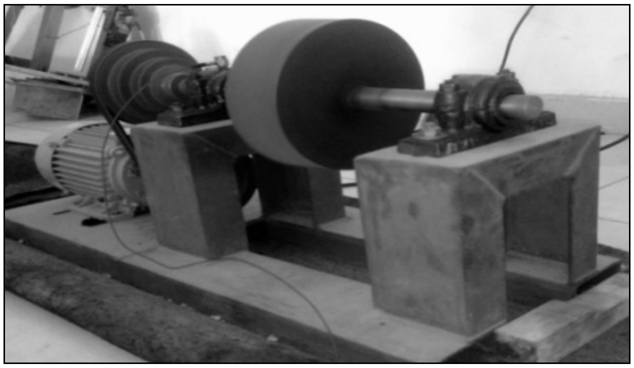


Figure 2. Experimental setup.

to failure at rated speeds (1400 RPM)and rated axial loads (0.2 kN). The vibration signals from the bearings are collected through the accelerometers placed on the either side of the housings and acquired via DAQ card. These signals were processed in the Labview. The experiment was run in real time conditions matching to the said bearing application. Adequate measures were taken to avoid bearing faults or damages due to fitments, misalignments etc,. All researches done on bearing life time mostly opts with Vibration signal as it is most effective and suitable for reflecting actual bearing running condition. There are other methods other than vibration signals such as temperature, oil or debris, acoustic methods etc to assess the health condition of the bearings. However vibration signals are less complex when compared to others. The amplitude of the vibration signals is monitored on a daily basis for estimating the current health condition of the bearings. The amplitude reflects the age of the bearing under study. The amplitude of the vibration is small and smooth when the bearing is under normal condition. The amplitude of the vibration signal gradually increases with respect to the time as shown in Figure 2. Meanwhile any defects or damages on the bearings during the process can also be easily identified if the acquired signals are contuniously monitored. Thus, vibration signal becomes the suitable variable to asses teh health condition of the bearings. The collected data from the bearings was categorized into different stages with respect to the time. The frequencies are defined as stage 1, stage 2, stage 3, stage 4 and stage 5 etc.... Signals acquired from a new bearing were placed on stage 1. Stage 2 and 3 includes the signals that are extracted from the bearing after 1000 hours and 1250 hours respectively. Stage 4 includes the signals that are extracted after 1500 hours of running the bearing at rated load and speed conditions. Signals from damaged bearing place in stage 5. The variations in signals, thus acquired for the bearings in various stages is shown in Figure 3 (a), 3 (b), 3 (c), 3 (d) and 3 (e) respectively.

4. Feature Description

The vibration signals acquired from the experiments are transformed to statistical features such as mean, median, mode, standard error, standard deviation, range, minimum, maximum, skewness, kurtosis, sum and sample variance. These 12 descriptive features were referred as features in this paper. Descriptions and definitions about the statistical features were detailed by Jegadeeshwaran & Sugumaran[17].

(a) Standard error: Standard error is the measure of the variance in the sampling distribution. The variance in the prediction of mean Y over the other parameter X in the regression, where *x* and *y* are the sample means and '*n*' is the sample size.

$$\text{Standard error of the predicted, } Y = \sqrt{\frac{1}{n-2}\left[\Sigma\left(y-\overline{y}\right)^2 - \frac{\left[\Sigma\left(x-\overline{x}\right)\left(y-\overline{y}\right)\right]^2}{\left(x-\overline{x}\right)^2}\right]} \quad (1)$$

(b) Standard deviation: This is a measure to quantify the variation in the data set. Standard deviation determines the closeness to the mean. Standard deviation value close to 0 means that the variation is less and increase in the value refers to high variance in the data set.

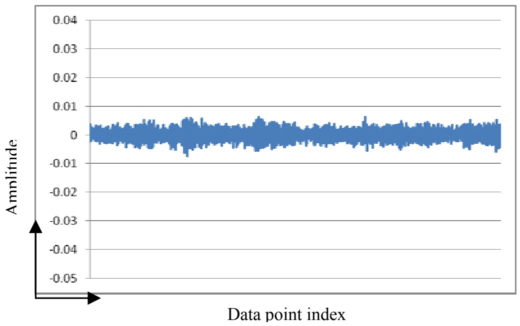
$$\text{Standard Deviation} = \sqrt{\frac{\sum x^2 - \left(\sum x\right)^2}{n(n-1)}} \quad (2)$$

(c) Sample variance: Sample variance is computed when there is enormous amount of data. A sample data from the population is considered for computing the sample variance.

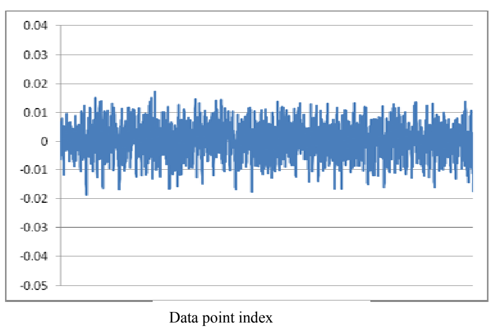
$$\text{Sample Variance} = \frac{\sum x^2 - \left(\sum x\right)^2}{n(n-1)} \quad (3)$$

(d) Kurtosis: Kurtosis is the measure that indicates the outliers in the data sets. The spikeness value in the data set in relation to normal distribution is measured. In vibration analysis, kurtosis directly reflects the health condition of the system.

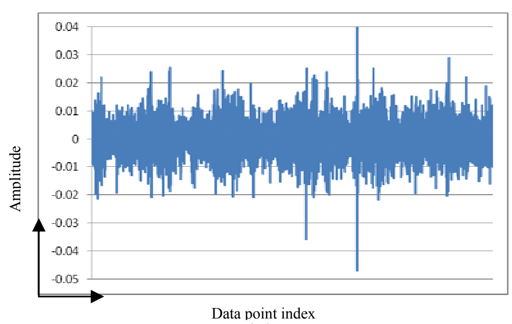
$$\text{Kurtosis} = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\Sigma\left(\frac{x_i-\overline{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (4)$$



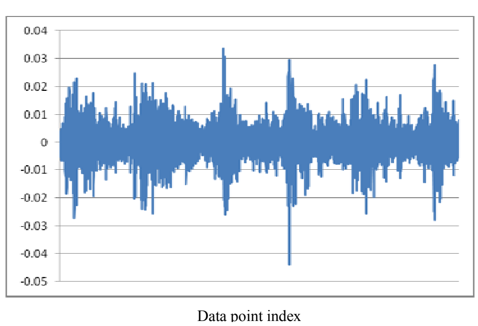
(a)



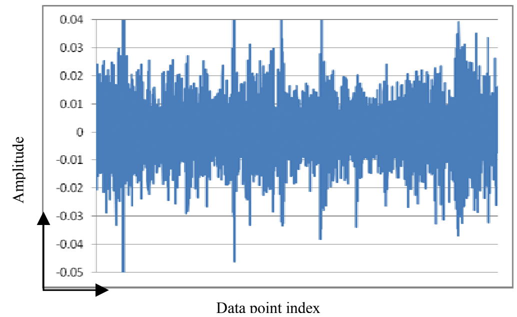
(b)



(c)



(d)



(e)

Figure 3 **(a)** Satge-1: Vibration Signals at Start. **(b)** Satge-2: Vibration signals@1000 Hrs. **(c)** Stage-3: Vibration Signals@1250Hrs. **(d)** Stage-4: Vibration Signals@1500Hrs. **(e)** Stage-5: Vibration Signals @1800 Hrs.

Where' s' is the sample standard deviation.

(e) Skewness: Skewness is a measure of lack of symmetry in the data set. The entire data set is skeweed towards left or right in the distribution.

$$\text{Skewness} = \frac{n}{n-1}\sum\left(\frac{x_i - \overline{x}}{s}\right)^3 \quad (5)$$

(f) Range: It measures the difference between the largest value and smallest value in the data set.

(g) Minimum value: It refers to the smallest observed value in the data set.

(h) Maximum value: It refers to the largest observed value in the data set. In vibration analysis, the minimum and maximum refers to the outliers which usually referred as faulty conditions.

(i) Sum: It refers to the addition of all data values in the population.

5. Feature Selection

Feature selection is the process of selecting best feature which has more information gain. Also the selected feature would be the best contributing feature, amid the rest of the features. This process is also termed as dimensionality reduction. This paper uses 12 descriptive statistical features as detailed in previous section. These features are extracted from the vibration signals and the best contributing feature with more information gain tops the list. Feature selection is performed with J48 Decision tree which is already proven as one the best available decision tree for feature selection[18-19]. In classification model, the feature that tops the list woud be on top of the decision tree and followed by the next best feature. The decision tree is thus visualized is shown below in Figure 4. This decision tree helps to select the features which contributes to the accuracy of the model, leaving behind the rest of the features. The selected features were arranged sequentially i.e the best feature in top and the least next to it. There are situations wherein all 12 features may not appear in the tree structure. Hence the left out features are considered to be the non value added features. An experiment was carried out by using only the top most features and classification accuracy is noted down, then top two features are selected and corresponding classification accuracy is noted. The process is continued till the classification accuracy of all the features are noted (refer Figure 5). It is found that 8 features, namely standard deviation, maximum, sum, Range, kurtosis, mean, median and minimum was found to be the best contributing features.

6. Building and Testing of Proposed Model

Regression is the most commonly used analysis technique for predictions and forecast. Regression is used to measure the relationship between two or more variables. Regression done with two variables is termed as simple regression. This regression helps to understand the variation in a dependent variable using the variation in independent variable. A simple regression fits a straight line to the data. The simple regression relationship between X and Y is given by

$$Y= a+bX \tag{6}$$

Where the symbol Y represents the predicted value of Y for a given value of X.

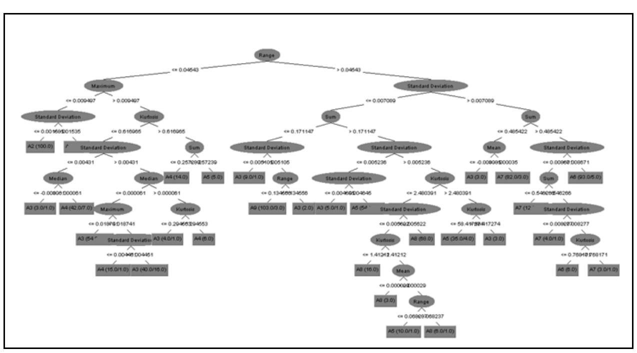


Figure 4. Decision Tree using J48 Algorithm.

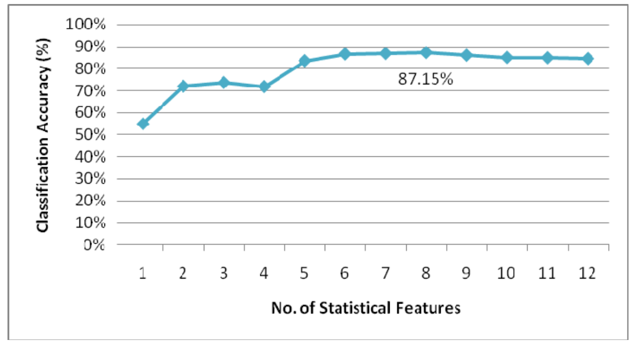


Figure 5. Classification Accuracy (%) vs. No. of Statistical features.

When more than one independent variable is used to derive the variance of the dependent variable, the relationship is well-defined as multiple correlation and the equation relating such relationship as a multiple regression equation. The multiple regression equation is expressed in the form

$$Y= a+b1X1 +b2X2 \tag{7}$$

Where $X1$ and $X2$ are two independent variables and Y being the dependent variable and $a,b1,b2$ are the constants.

The concept of Support Vector Machines (SVM) was initially coined by Vapnik (1995). The SVM is a supervised learning models which can analyze data and recognize the patterns. This model was commonly used for classification problems and later applied for regression analysis also. Support vector machine is mostly preferred method as it is able to transform the problem with the use of few kernel equations such that we shall relate linear classification methods to non-linear data. The various kind of data instances in a multidimensional space are separated by a hyper plane with the aid of kernel equations. These kernel equations shall be linear or Gaussian so that the non seperable data in one domain is transformed to other domain where the data becomes seperable. The ultimate aim of dividing this data into two categories is to arrive at a hyper plane that seperates the data. This plane is critical as it decides the value of the predictor variables. The place that has a wide margin between the support vectors is selected. Thus the SVR model helps us to predict the unknown variables on the said principles.

The vibration signals that are acquired at defined intervals from the bearings mounted on the experimental setup was extracted through descriptive statistical

Table 1. Results of Regression Model using Support vector machine

Correlation coefficient	0.961
Mean absolute error	0.272
Root Mean Squared Error	0.3848
Relative absolute error	1.5037%
Root Relative squared error	0.5332%
Total number of Instances	900

features. These features are used to assess the health state of the bearings. Later the best contributing features which has more information gain are selected using decision tree. A predictive model is built with the selected statistical features using Support Vector Regression along with normalised poly kernel functions. This model was tested under 10 fold cross validation for better accuracies. The Table 1 lists out the outcome of the proposed model. In an ideal system, the correlation coefficient closeness to 1 reflects that the model built is precise. The correlation coefficient measures the strength of association between the selected variables. The correlation coefficient of this model is 0.961. Totally, 378422 number of kernel evaluations were done. The time taken to built this model is 17.45 seconds. This model was tested with 900 instances that was acquired at defined intervals. Mean Absolute Errors (MAE) measure, the closeness value of predictions to the eventual outcomes. Root Mean Squared Error (RMSE) is a common metric for numeric predictions. This is the measure of difference between the forecast values and actuals. The MAE and RMSE are performance indice that analyzes the variance in predictions. The RMSE value will be always greater than MAE value. The greater the difference the more the variation in the dataset.

7. Conclusion

Bearings play a vital role in most of the rotating machineries. Estimating the life time of bearings and monitoring the health condition of the bearings are widely accepted by the industries and well received in the recent times. This paper presented a predictive method to estimate the remaining useful life the bearings based on Support Vector regression. This method is based on the data driven prognostics. The bearings are made to run at stated conditions that are similar to real time applications. The vibration signals are acquired at defined intervals till the bearing fails naturally. Statistical features were extracted and top contributing features are selected using the decision tree algorithm. Thus selected features are used to construct the model based on the support vector regression. The predictive model built on the SVR yield correlation coefficient 0.961 that is utmost par with all other available predictive models. This model that was tested with the bearing life data can also be horizontally deployed for predicting the remaining life of all other critical components.

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